A

Research Synopsis

On

HYBRID MACHINE LEARNING TECHNIQUE FOR PERSON IDENTIFICATION USING MULTIMODEL PALMPRINT, EAR AND FACE BIOMETRIC FEATURES

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1. Introduction

In modern trends, all systems require reliable personal identification programs to verify or determine a person's identity. The purpose of the Personal Identity Program is to ensure that the services provided are only available to authentic real users [1]. Automated authentication technologies are extensive in any application related to security based on a person's behavior and physical characteristics. Biometric systems provide access to physical rights, information, services and other rights or benefits. Therefore, these systems use traits that seek to identify a person's privacy, legal and social factors [2][3]. The two categories of biometric identifiers include physiological and behavioral characteristics. A physiological biometric would be identified by one's Face, Iris, voice, DNA or handprint. Behavior Biometrics is related to human behavior such as typing, walking, voice, handwriting and so on. Biometric technology is now used in almost all fields [4].

Many popular biometric technology programs in government agencies include birth certificates, naturalization sheets, passports, identity cards, and other government-issued documents proving citizenship. Multimodal biometric systems provide an alternative when noise sensor data, variations of lighting, pricing for various events, biometric features and fraud attacks cannot be easily understood by a person [5]. In addition, additional information can be provided through various biometrics, resulting in a higher identification system. In fact, a multi biometric system can be divided into four categories: multiple sensors, multiple models, multiple mechanisms, and multiple events [6].

Linking information from multiple biometric sources is called information fusion. This can be divided into three different level combinations. At the sensor level, the fusion process takes place in front of the recovery module, and this can only be done if the various acquisitions are instances of the same biometric module derived from multiple compatible sensors. Character-level merging is the process of combining different characteristic vectors generated from different biometric models to form a single model or characteristic vector [7][8]. Only in the case of mutually compatible or homogeneous characteristic vectors can they be combined as a characteristic vector. The score level is matched after the competition module has created

competition scores between the test sample and the sample stored in the database as an indicator of similarity or difference for each sample system. Recently, identification systems based on biometrics and security concerns have become areas of research interest. Because of the similarities between individuals, most studies in the literature review focus on fingerprints, face, fingerprints, and iris [9]. In particular, the challenges of facial recognition include appearance, age changes, beard and makeup. Ear images are less susceptible to changes in appearance or makeup than face images, and the combination of face / ear recognition gives less recognition and is easier to understand by recognizing face and ear [10].

In recent years, there have been several approaches combining two or three biometric properties. Multimodal biometric finger recognition integrates the functions of fingerprint, fingerprint, finger shape and finger-to-finger printing from a human finger. Multimodal biometrics provides a point-level fusion approach [11] is based on a triangular standard with a four-finger biometric mark. The ROI local gradient system (SLG) of the Palmer axis and the annual axis are derived and modified using the brand, which allows for a strong image of a strong V code and an image of an index h [12]. The confidence-based late integration framework used for audiovisual biometrics [13] shows that competitive confidence can be calculated from competitive confidence scores and that a coefficient C can be calculated to convert competitive scores. The voice recognition model was developed using two well-known speakers, MFCC and PLP, both of which are used with GMM. The facial recognition model is based on clean face and Euclidean distance (EUD) [14]. Despite their important role in forensic and biometric applications, previous studies on lip prints have yielded very few results [15]. The multimodal detection system is based on the Multiple Vector Neural Network (MSVNN) based on Chloe Penguin search optimization algorithm [16]. The multimodal single-sensor approach to manual venous-based biometric detection is challenged. Image of hand nerves, structured palmar nerve and four ROIs of finger nerve were obtained [17]. The integration scheme [18] is used as a multimedia biometric system for human recognition to distinguish sounds and faces. The sound recognition process shows that the best results are obtained by simulating septal coefficients using the GMM classifier display. A multimodal biometric algorithm designed to integrate iris, palm print, face and signature based on converting individual waves encoded for image analysis and recognition [19]. A multimodal biometric system based on the optimal score level fusion model. The main idea of this article is to optimally integrate three additional biometric properties

of the iris, fingernail, and fingerprint, which can be optimized using the optimization algorithm of backtracking search optimization algorithm (BSA) [20].

2. Review of Literature and Development in the subject

Ma et al. [21] have proposed a discriminant orientation and scale features learning (DOSFL) for palmprint recognition. By introducing the idea of discriminant analysis into palmprint coding, DOSFL can extract the orientation and scale features with more favorable discriminability. Then, DOSFL utilizes four code bits to represent both the orientation and scale features of palmprint, and employs the Hamming distance for code matching. A multi-orientation and multi-scale features discriminant learning (MOSDL) approach used for palmprint recognition, which fuse different orientation and scale feature information effectively in the discriminant learning process. Liang et al. [22] have proposed an orientation-space code scheme to represent the orientation space feature of palmprint and designed a multi-feature two-phase sparse representation (MTPSR) scheme for feature matching. MTPSR combined with proposed orientation space based feature is more effective than state-of-art sparse representation methods. Moreover, both the excellent accuracy of the proposed method in the case of few training samples, and the low time consumption indicates that it is suitable for real-world applications. Aleem et al. [23] have proposed a local non-negative matrix factorization (LNMF) for dimensionality reduction of face subspace. The face and finger print biometric traits are used to construct a multimodal biometric recognition system. These two modalities are selected as they are most natural and acceptable means of biometrics. The elastic alignment algorithm is used to extract features from finger image. Fusion of the chosen modalities is performed at the matching score level. The success of face recognition is highly reliant on the representation of high-dimensional face space. An efficient way is to find intrinsically low-dimensional subspace that effectively represents the underlying data. LNMF not only achieves the dimensionality reduction by part based representation, but also focuses to preserve the local information, adds sparsity, retian only the most significant basis and provides more true parts based representation.

Kushwaha et al. [24] have described usage of footprint biometrics using description of foot contour and different shape features as foot descriptors consisting of province, major axis, minor axis, eccentricity and centroid of foot. Then computed different variations of weighted sum rule

on shape descriptors and fused each variation with foot contour features. The experiments showed that the variation with maximum weight to province performs better when fused with foot contour feature. The best variation provides GAR 82%. Another feature based on GLCM is also introduced, which increase the GAR to 87.5% at 2.0% FAR. Chanukya et al. [25] have proposed an innovative optimal neural network based biometric image classification method with three diverse phases such as the Preprocessing, Feature Extraction and classification. This technique commences with the task of preprocessing involving the median filters. It is followed by the feature extraction stage in which various features are effectively extorted from the biometric images. The extracted features include the shape and texture feature like the fingerprint and ear feature. ONN technique admirably classifies the images. The efficiency metrics such as the false positive rate, false negative rate, sensitivity, specificity and accuracy are successfully estimated for the new-fangled technique, which comes out in flying colors in classifying the images with superlative efficacy, thereby accomplishing sterling efficiency in the task of classification of images and turning out cheering outcomes of amazing accuracy.

Shende et al. [26] proposed a convolutional neural network (CNN) based face, fngerprint, palm vein identifcation system. Main purpose of this paper is to propose a convolutional neural network with minimum layers for face, fingerprint and palm vein, achieving high accuracy and reducing the complexity. The network is of two convolutional layers, two ReLU layers and two Maxpooling layers with ten hidden layers in fully connected layer. The dataset of 4500 images is generated for all the modalities. Dataset images are used for 60% training, 10% validation and testing 30%. Proposed CNN architecture's accuracy is 95% for face, 94% for fingerprint and 99% palm-vein. Rahman et al. [27] have concerned to study the performance of different classification techniques and fusion rules in the context of unimodal and multimodal biometric systems based on the ECG and fingerprint. The experiments are conducted on ECG and fingerprint databases to evaluate the performance of the proposed biometric systems. MIT-BIH database is utilized for ECG, FVC2004 database is utilized for the fingerprint, and further experiments are being performed to evaluate the proposed multimodal system with 47 subjects from virtual multimodal database. The performance of the uni-modal and multimodal biometric systems is measured using receiver operating characteristic curve, AUC, sensitivity, specificity, efficiency, standard error of the mean, and likelihood ratio.

Table 1 Summary of research gap

Ref.	Model	Features	Key algorithm.	Parameter	Remarks
[21]	Uni-modal	Palmprint	DOSFL	GAR, EER and Average recognition rate	The lighting may be changing and low, the multi-spectral samples
[22]	Uni-modal	Palmprint	MTPSR	Accuracy and computational cost	No efforts had been made to improve the performance of two-phase framework.
[23]	Multi-modal	Face and finger print	LNMF	EER, FAR and FRR	Distance to surveillance camera, equipment and operator training can significantly affect the performance
[24]	Uni-modal	Foot	GLCM	GAR and accuracy	Dynamic time warping for classification.
[25]	Multi-modal	Fingerprint and ear	ONN	Accuracy, sensitivity and specificity	Consistent authentication has assumed zooming significance in today's world.
[26]	Multi-modal	Face, fingerprint, palm vein	CNN	Accuracy and EER	While increase in training Samples it affects more on accuracy.
[27]	Multi-modal	ECG and fingerprint	Decision-level fusion	Accuracy and ROC	The total number of biometric modalities required for identification is increased.
[28]	Uni-modal	Face	ANN, SVM	EER	The biometrics security is not suitable for the WBAN nodes
[29]	Uni-modal	Hand Radiograph	KNN, SVM	Accuracy	It becomes a time-consuming and challenging task to select a particular algorithm.
[30]	Uni-modal	Footprint	FSVM, FKNN and FESD	Accuracy	Biometric trait and uniqueness affect the single biometric systems

El-Bendary et al. [28] have presented multimodal scheme is evaluated and applied using the feature and score fusion. The function of the mechanism of the given algorithm begins by taking the "face / sound" of the biometric signals, the second step being the characteristic of removing each person from the biometrics. A synthetic neural network (ANN), a support vector machine (SVM) and a Gaussian compound model (GMM) classifier were used to classify separately. Computer simulation tests show that the celestial coefficients and statistical coefficients for sound recognition work best on a sound display. In addition, in the facial recognition program,

the Eigen facial and sub-vector tools performed better than other circuits. Joshi et al. [29] proposed a forensic hand radiograph based human authentication is proposed using a deep neural network. The three-tier transformation deep neural network structure is used to obtain manual radiographic features and to determine the KNN and SVM classifiers. As part of the experiment, a total of 750 freehand radiographs from 150 subjects of different ages, occupations and genders were examined. The performance of the algorithm is evaluated according to the accuracy of cross-checking according to the pixels of different strings, the size of the voting window, the size of the kernel and the number of filters. Basheer et al. [30] have proposed algorithm utilizes the fuzzy logic-based method for personal identification. 220 companies with temporary feature to fill the void of existing methods will be taken into account. Magnificent Gaussian SVM, Fine KNN (FKNN) and Fuzzy ensemble sub-dimensional space (FES) to create an advanced human footprint .T) three approaches are used. The summary of research gap is given in Table 1.

3. Objectives of Research / Proposed Hypothesis

The main objectives of proposed technique are list as follows:

1. To introduce novel hybrid machine learning technique for person identification using multi-model biometrics.
2. To study and analyze the image pre-processing algorithms to enhance the quality of input image.
3. To introduce optimization technique for feature fusion to improve the detection accuracy.
4. To propose hybrid neural network based classifier to predict the person which is more suitable for medical application such as dead body identification. Forensic and etc.

4. Methodology to be adopted

Lohith et al. [31] have proposed a multimodal biometrics for person identification using ear and palm print features. Both of these methods can improve authentication performance because they provide the most important and unique features. The area of the palm is very distinctive because the area of the palm is larger than the ear area, so at the same level, low-resolution ear images work faster. The local description and feature level used to extract features from ear and pamphlet images are linked to LPP and BSIF.

Experimental studies show that multimodal biometrics provide better identification ratios compared to unimodal biometrics. In general, multimodal biometric authentication effectively modifies the single-mode biometric authentication system to address a wide range of technical limitations in identity management and authentication. Legitimacy plays an important role in the banking, military and healthcare sectors in terms of highly secure, strategic and confidential data transfer. Fraudulent issues can be solved through a combination of several independent biometric systems. There are basically four components to a typical biometric system pre-processing, separation of functions, customization, and completion phase. The function extraction method significantly affects the performance of the system; there are ways to separate several functions.

The literature found that many researchers used only two biometric features for experimental study. Now, some innovative applications, such as the Adhar card system, use facial, finger, and iris functions to identify a person. In the future, to improve accuracy, most systems will combine more than two biometric features to identify people.

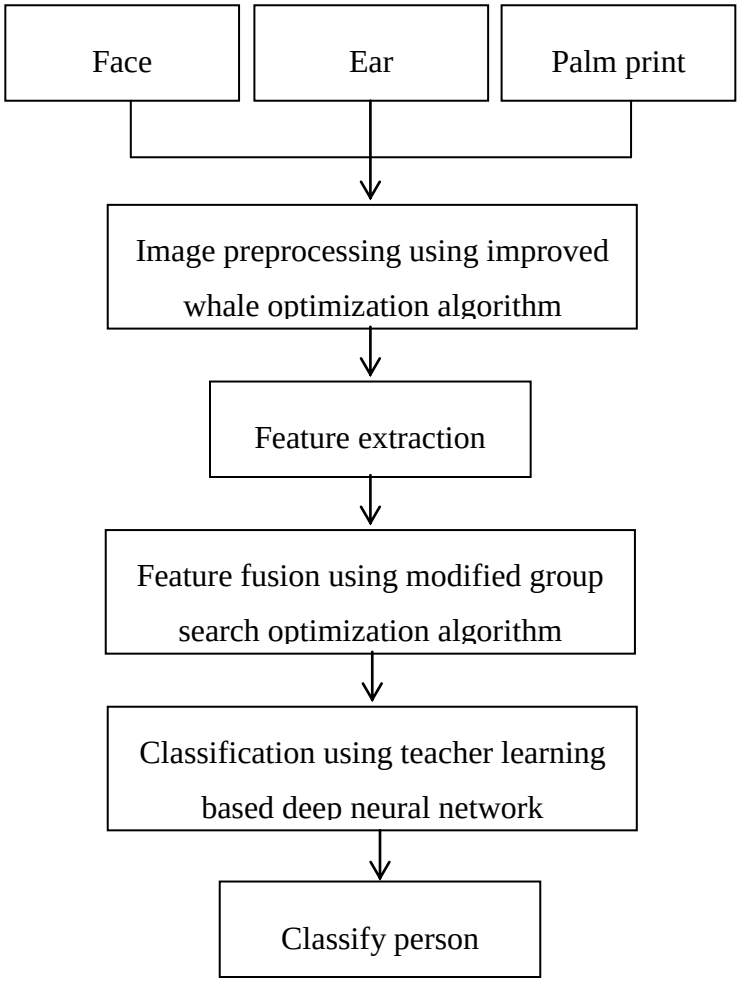

Fig.1. Methodology of Proposed HML-PI.

For further enhance the detection accuracy and performance enhancement, we propose a hybrid machine learning technique for person identification (HML-PI) using multimodal palm print, ear and face biometric features.

The main contributions of the proposed HML-PI technique are given as follows:

1. First, we introduce an improved whale optimization (IWO) algorithm for image preprocessing which remove unwanted artifacts and noise from the raw input image.
2. After the feature extraction, we develop a modified group search optimization (MGSO) algorithm to optimize the features to obtain best optimal features among multiples which reduces the dimensionality problems.
3. Then, we introduce a teacher learning based deep neural network (TL-DNN) technique for person detection which enhances the prediction accuracy and reduce all error metrics.
4. Finally, the proposed TL-DNN technique can be compared with the existing state-of-art techniques in terms of different performance metrics are accuracy, precession, recall and f-measure; error metrics are EER, FAR and FRR.

5. Importance of Study / Society application

The main limitations of a centralized cloud environment are data security, complete computer management, lost storage on personal portable devices, and system capabilities. Within these limits, security raises serious concerns about unauthorized access to personal data. In particular, biometric data is considered important data and its use is subject to the Privacy Act. To solve this problem, a multimodal authentication system using cryptographic biometrics for edge-to-edge cloud environments was suggested in this study. The error rate of a sorting system is usually reported as a function of the percentage of the database that the system should search for. The confusing matrix classifier provides detailed behavioral analysis. Medical Purpose: The recognition of forensic palm prints related to the printing of high-resolution palm prints and the comparison of hidden whole palm prints has led to major research into the increasing use of palm fingerprints in forensics. There are some detailed operations in high resolution palm print processing and function extraction.

6. Proposed work Plan / Formulation and Structure of Study:

The proposed work is to implement digital image processing techniques by using computing tool Matlab-2019.

Tentative phase wise plan of proposed study we have designed as per the convenience of the study.

Phase 1:

1. Collection of images provides the Hong Kong Polytechnic University (PolyU) 2D_Palmprint, Face and Ear Database.

Phase 2:

1. We introduce an improved whale optimization (IWO) algorithm for image preprocessing which remove unwanted artifacts and noise from the raw input image.

Phase 3:

1. After the feature extraction, we develop a modified group search optimization (MGSO) algorithm to optimize the features to obtain best optimal features among multiples which reduces the dimensionality problems.

Phase 4:

1. Then, we introduce a teacher learning based deep neural network (TL-DNN) technique for person detection which enhances the prediction accuracy and reduce all error metrics.

Phase 5:

1. Finally, the proposed TL-DRNN technique can be compared with the existing state-of-art techniques in terms of different performance metrics are accuracy, precession, recall and f-measure; error metrics are EER, FAR and FRR.

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